can be substantially improved by using successive observations over a period of time. This can either be accomplished by averaging the data prior to insertion into a neural network, or alternately the decision of the neural network can be averaged. This is known as the categorization phase of the process. During categorization the occupancy state of the vehicle is determined. Is the vehicle occupied by the forward facing human, an empty seat, a rear facing child seat, or an out-of-position human? Typically many seconds of data can be accumulated to make the categorization decision.

When a driver senses an impending crash, on the other hand, he or she will typically slam on the brakes to try to slow vehicle prior to impact. If an occupant is unbelted, he or she will begin moving toward the airbag during this panic braking. For the purposes of determining the position of the occupant, there is not sufficient time to average data as in the case of categorization. Nevertheless, there is information in data from previous vectors that can be used to partially correct errors in current vectors, which may be caused by thermal effects, for example. One method is to determine the location of the occupant using the neural network based on previous training. The motion of the occupant can then be compared to a maximum likelihood position based on the position estimate of the occupant at previous vectors. Thus, for example, perhaps the existence of thermal gradients in the vehicle caused an error in the current vector leading to a calculation that the occupant has moved 12 inches since the previous vector. Since this could be a physically impossible move during ten milliseconds, the measured position of the occupant can be corrected based on his previous positions and known velocity. Naturally, if an accelerometer is present in the vehicle and if the acceleration data is available for this calculation, a much higher accuracy prediction can be made. Thus, there is information in the data in previous vectors as well as in the positions of the occupant determined from the this data that can be used to correct erroneous data in the current vector and, therefore, in a manner not too dissimilar from the averaging method for categorization, the position accuracy of the occupant can be known with higher accuracy.

Returning to the placement of ultrasonic transducers for the ultrasonic occupant position sensor system, as to the more novel features of the invention for the placement of ultrasonic transducers, this application discloses (1) the application of two sensors to single-axis monitoring of target volumes; (2) the method of locating two sensors spanning a target volume to sense object positions, that is, transducers are mounted along the sensing axis beyond the objects to be sensed; (3) the method of orientation of the sensor axis for optimal target discrimination parallel to the axis of separation of distinguishing target features; and (4) the method of defining the head and shoulders and supporting surfaces as defining humans for rear facing child seat detection and forward facing human detection.

A similar set of observations is available for the use of electromagnetic sensors. Such rules however must take into account that such sensors typically are more accurate in measuring lateral and vertical dimensions relative to the sensor and distances perpendicular to the sensor. This is particularly the case for CMOS and CCD based transducers.Considerable work is ongoing to improve the resolution of the ultrasonic transducers. To take advantage of higher resolution transducers, more closer together data points should be obtained. This means that after the envelope has been extracted from the returned signals, the sampling rate should be increased from approximately 1000 samples per second to perhaps 2000 samples per second or even higher. By doubling or tripling the amount data required to be analyzed, the system which is mounted on the vehicle will require greater computational power. This results in a more expensive electronic system. Not all of the data is of equal importance, however. The position of the occupant in the normal seating position does not need to be known with great accuracy whereas as that occupant is moving toward the keep out zone boundary during pre-crash braking, the spatial accuracy requirements become more important. Fortunately, the neural network algorithm generating system has the capability of indicating to the system designer the relative value of each of the data points used by the neural network. Thus, as many as, for example, 500 data points per vector may be collected and fed to the neural network during the training stage and, after careful pruning, the final number of data points to be used by the vehicle mounted system may be reduced to 150, for example. This technique of using the neural network algorithm-generating program to prune the input data is an important teaching of the present invention. By this method, the advantages of higher resolution transducers can be optimally used without increasing the cost of the electronic vehicle mounted circuits. Also, once the neural network has determined the spacing of the data points, this can be fine-tuned, for example, by acquiring more data points at the edge of the keep out zone as compared to positions well into the safe zone. The initial technique is done be collecting the full 500 data points, for example, while in the system installed in the vehicle the data digitization spacing can be determined by hardware or software so that only the required data is acquired.

The technique that was described above for the determination of the location of an occupant during panic or braking pre-crash situations involved the use of a modular neural network. In that case, one neural network was used to determine the occupancy state of the vehicle and the second neural network was used to determine the location of the occupant within the vehicle. The method of designing a system utilizing multiple neural networks is a key teaching of the present invention. When this idea is generalized, many potential combinations of multiple neural network architectures become possible. Some of these will now be discussed.

One of the earliest attempts to use multiple neural networks was to combine different networks trained differently but on substantially the same data under the theory that the errors which affect the accuracy of one network would be independent of the errors which affect the accuracy of another network. For example, for a system containing four ultrasonic transducers, four neural networks could be trained each using a different subset of the four transducer data. Thus, if the transducers are arbitrarily labeled A, B, C and D the then the first neural network would be trained on data from A, B and C. The second neural network would be trained on data from B, C, and D etc. This technique has not met with a significant success since it is an attempt to mask errors in the data rather than to eliminate them. Nevertheless, such a system does perform marginally better in some situations compared to a single network using data from all four transducers. The penalty for using such a system is that the computational time is increased by approximately a factor of three. This significantly affects the cost of the system installed in a vehicle.

An alternate method of obtaining some of the advantages of the parallel neural network architecture described above, is to form a single neural network but where the nodes of one or more of the hidden layers are not all connected to all of the input nodes. Alternately, if the second hidden layer is

chosen, all of the notes from the previous hidden layer are not connected to all of the nodes of the subsequent layer. The alternate groups of hidden layer nodes can then feed to different output notes and the results of the output nodes combined, either through a neural network training process into a single decision or a voting process. This latter approach retains most of the advantages of the parallel neural network while substantially reducing the computational complexity.

The fundamental problem with parallel networks is that they focus on achieving reliability or accuracy by redundancy rather than by improving the neural network architecture itself or the quality of the data being used. They also increase the cost of the final vehicle installed systems. Alternately, modular neural networks improve the accuracy of the system by dividing up the tasks. For example, if a system is to be designed to determine the type of tree and the type of animal in a particular scene, the modular approach would be to first determine whether the object of interest is an animal or a tree and then use separate neural networks to determine type of tree and the type of animal. When a human looks at a tree he is not ask himself is that a tiger or a monkey. Modular neural network systems are efficient since once the categorization decision is made, the seat is occupied by forward facing human, for example, the location of that object can be determined more accurately and without requiring increased computational resources.

Another example where modular neural networks have proven valuable is provide a means for separating "normal" from "special cases". It has been found that in some cases, the vast majority of the data falls into what might be termed "normal" cases that are easily identified with a neural network. The balance of the cases cause the neural network considerable difficulty, however, there are identifiable characteristics of the special cases that permits them to be separated from the normal cases and dealt with separately. Various types of human intelligence rules can be used, in addition to a neural network, to perform this separation including fuzzy logic, statistical filtering using the average class vector of normal cases, the vector standard deviation, and threshold where a fuzzy logic network is used to determine chance of a vector belonging to a certain class. If the chance is below a threshold, the standard neural network is used and if above the special one is used.

Mean-Variance connections, Fuzzy Logic, Stochastic, and Genetic Algorithm networks, and combinations thereof such as Neuro-Fuzzy systems are other technologies considered. During the process of designing a system to be adapted to a particular vehicle, many different neural network architectures are considered including those mentioned above. The particular choice of architecture is frequently determined on a trial and error basis by the system designer. Although the parallel architecture system described above has not proven to be in general beneficial, one version of this architecture has shown some promise. It is known that when training a neural network, that as the training process proceeds the accuracy of the decision process improves for the training and independent databases. It is also known that the ability of the network to generalize suffers. That is, when the network is presented with a system which is similar to some case in the database but still with some significant differences, the network may make the proper decision in the early stages of training, but the wrong decisions after the network has become fully trained. This is sometimes called the young network vs. old network dilemma. In some cases, therefore, using an old network in parallel with a young network can retain some of the advantages of both networks, that is, the high accuracy of the old network coupled with the greater generality of the young network. Once again, the choice of any of these particular techniques is part of the process of designing a system to be adapted to a particular vehicle and is the prime subject of this invention. The particular combination of tools used depends on the particular application and the experience of the system designer.

The methods above have been described in connection with the use of ultrasonic transducers. Many of the methods, however, are also applicable to optical, radar, capacitive and other sensing systems and where applicable, this invention is not limited to ultrasonic systems. In particular, an important feature of this invention is the proper placement of three or more separately located receivers such that the system still operates with high reliability if one of the receivers is blocked by some object such as a newspaper. This feature is also applicable to systems using electromagnetic radiation instead of ultrasonic, however the particular locations will differ based on the properties of the particular transducers. Optical sensors based on two-dimensional cameras or other image sensors, for example, are more appropriately placed on the sides of a rectangle surrounding the seat to be monitored rather than at the corners of such a rectangle as is the case with ultrasonic sensors. This is because ultrasonic sensors measure an axial distance from the sensor where the camera is most appropriate for measuring distances up and down and across its field view rather than distances to the object. With the use of electromagnetic radiation and the advances which have recently been made in the field of very low light level sensitivity, it is now possible, in some implementations, to eliminate the transmitters and use background light as the source of illumination along with using a technique such as auto-focusing to obtain the distance from the receiver to the object. Thus, only receivers would be required further reducing the complexity of the system.

Although implicit in the above discussion, an important feature of this invention which should be emphasized is the method of developing a system having distributed transducer mountings. Other systems which have attempted to solve the rear facing child seat (RFCS) and out-of-position problems have relied on a single transducer mounting location or at most, two transducer mounting locations. Such systems can be easily blinded by a newspaper or by the hand of an occupant, for example, which is imposed between the occupant and the transducers. This problem is almost completely eliminated through the use of three or more transducers which are mounted so that they have distinctly different views of the passenger compartment volume of interest. If the system is adapted using four transducers as illustrated in the distributed system of FIG. 9, for example, the system suffers only a slight reduction in accuracy even if two of the transducers are covered so as to make them inoperable.

It is important in order to obtain the full advantages of the system when a transducer is blocked, that the training and independent databases contains many examples of blocked transducers. If the pattern recognition system, the neural network in this case, has not been trained on a substantial number of blocked transducer cases, it will not do a good job in recognizing such cases later. This is yet another instance where the makeup of the databases is crucial to the success of designing the system that will perform with high reliability in a vehicle and is an important aspect of the instant invention.

Other techniques which may or may not be part of the process of designing a system for a particular application include the following:

1. Fuzzy Logic

As discussed above, neural networks frequently exhibit the property that when presented with a situation that is totally different from any previously encounter, an irrational decision can result. Frequently when the trained observer looks at input data, certain boundaries to the data become evident and cases that fall outside of those boundaries are indicative of either corrupted data or data from a totally unexpected situation. It is sometimes desirable for the system designer to add rules to handle these cases. These can be fuzzy logic based rules or rules based on human intelligence. One example would be that when certain parts of the data vector fall outside of expected bounds that the system defaults to an airbag enable state.

2. Genetic Algorithms

When developing a neural network algorithm for a particular vehicle, there is no guarantee that the best of all possible algorithms has been selected. One method of improving the probability that the best algorithm has been selected is to incorporate some of the principles of genetic algorithms. In one application of this theory, the network architecture and/or the node weights are varied pseudorandomly to attempt to find other combinations which have higher success rates. The discussion of such genetic algorithms systems appears in the book *Computational Intelligence* referenced above.

3. Pre-processing

For military target recognition is common to use the Fourier transform of the data rather than the data itself. This can be especially valuable for categorization as opposed to location of the occupant and the vehicle. When used with a modular network, for example, the Fourier transform of the data may be used for the categorization neural network and the non-transformed data used for the position determination neural network. Recently wavelet transforms have also been considered as a preprocessor.

4. Occupant Position Determination Comparison

Above, under the subject of dynamic out-of-position, it was discussed that the position of the occupant can be used as a filter to determine the quality of the data in a particular vector. This technique can also be used in general as a method to improve the quality of a vector of data based on the previous positions of the occupant. This technique can also be expanded to help differentiate live objects in the vehicle from inanimate objects. For example, a forward facing human will change his position frequently during the travel of the vehicle whereas a box will tend to show considerably less motion. This is also useful, for example, in differentiating a small human from an empty seat. The motion of a seat containing a small human will be significantly different from that of an empty seat even though the particular vector may not show significant differences. That is, a vector formed from the differences from two successive vectors is indicative of motion and thus of an occupant.

5. Blocked Transducers

It is sometimes desirable to positively identify a blocked transducer and when such a situation is found to use a different neural network which has only been trained on the subset of unblocked transducers. Such a network, since it has been trained specifically on three transducers, for example, will generally perform more accurately than a network which has been trained on four transducers with one of the transducers blocked some of the time. Once a blocked transducer has been identified the occupant can be notified if the condition persists for more than a reasonable time.

6. Other Basic Architectures

The back propagation neural network is a very successful general-purpose network. However, for some applications, there are other neural network architectures that can perform better. If it has been found, for example, that a parallel network as described above results in a significant improvement in the system, then, it is likely that the particular neural network architecture chosen has not been successful in retrieving all of the information that is present in the data. In such a case an RCE, Stochastic, Logicon Projection, or one of the other approximately 30 types of neural network architectures can be tried to see if the results improve. This parallel network test, therefore, is a valuable tool for determining the degree to which the current neural network is capable of using efficiently the available data.

7. Transducer Geometry

Another technique, which is frequently used in designing a system for a particular vehicle, is to use a neural network to determine the optimum mounting locations, aiming directions and field angles of transducers. For particularly difficult vehicles it is sometimes desirable to mount a large number of ultrasonic transducers, for example, and then use the neural network to eliminate those transducers which are least significant. This is similar to the technique described above where all kinds of transducers are combined initially and later pruned.

8. Data Quantity

Since it is very easy to take large amounts data and yet large databases require considerably longer training time for a neural network, a test of the variability of the database can be made using a neural network. If for example after removing half of the data in the database, the performance of a trained neural network against the validation database does not decrease, then the system designer suspects that the training database contains a large amount of redundant data. Techniques such as similarity analysis can then be used to remove data that is virtually indistinguishable from other data. Since it is important to have a varied database, it is undesirable generally to have duplicate or essentially duplicate vectors in the database since the presence of such vectors can bias system and drive the system more toward memorization and away from generalization.

9. Environmental Factors

An evaluation can be made of the beneficial effects of using varying environmental influences during data collection on the accuracy of the system using neural networks along with a technique such as design of experiments.

10. Database Makeup

It is generally believed that the training database must be flat meaning that all of the occupancy states that the neural network must recognize must be approximately equally represented in the training database. Typically, the independent database has approximately the same makeup as the training database. The validation database, on the other hand, typically is represented in a non-flat basis with representative cases from real world experience. Since there is no need for the validation database to be flat, it can include many of the extreme cases as well as being highly biased towards the most common cases. This is the theory that is currently being used to determine the makeup of the various databases. The success of this theory continues to be challenged by the addition of new cases to the validation database. When significant failures are discovered in the validation database, the training and independent databases are modified in an attempt to remove the failure.

11. Biasing

All seated state occupancy states are not equally important. The final system must be nearly 100% accurate for forward facing in-position humans. Since that will comprise the majority of the real world situations, even a small loss in

accuracy here will cause the airbag to be disabled in a situation where it otherwise would be available to protect an occupant. A small decrease in accuracy will thus result in a large increase in deaths and injuries. On the other hand, there are no serious consequences if the airbag is deployed occasionally when the seat is empty. Various techniques are used to bias the data in the database to take this into account. One technique is to give a much higher value to the presence of a forward facing human during the supervised learning process than to an empty seat. Another technique is to include more data for forward facing humans than for empty seats. This, however, can be dangerous as an unbalanced network leads to a loss of generality.

12. Screening

It is important that the loop be closed on data acquisition. That is, the data must be checked at the time the data is acquired to the sure that it is good data. Bad data can happen because of electrical disturbances on the power line, sources of ultrasound such as nearby welding equipment, or due to human error. If the data remains in the training database, for example, then it will degrade the performance of the network. Several methods exist for eliminating bad data. The most successful method is to take an initial quantity of data, such as 30,000 to 50,000 vectors, and create an interim network. This is normally done anyway as an initial check on the system capabilities prior to engaging in an extensive data collection process. The network can be trained on this data and, as the real training data is acquired, the data can be tested against the neural network created on the initial data set. Any vectors that fail are examined for reasonableness.

13. Vector Normalization Method

Through extensive research it has been found that the vector should be normalized based on all of the data in the vector, that is have all its data values range from 0 to 1. For particular cases, however, it has been fond desirable to apply the normalization process selectively, eliminating or treating differently the data at the early part of the data from each transducer. This is especially the case when there is significant ringing on the transducer or cross talk when a separate send and receive transducer is used. There are times when other vector normalization techniques are required and the neural network system can be used to determine the best vector normalization technique for a particular application.

14. Feature Extraction

The success of a neural network system can frequently be aided if additional data is inputted into the network . One example can be the number of 0 data points before the first peak is experience. Alternately, the exact distance to the first peak can be determined prior to the sampling of the data. Other features can include the number of peaks, the distance between the peaks, the width of the largest peak, the normalization factor, the vector mean or standard deviation, etc. These normalization techniques are frequently used at the end of the adaptation process to slightly increase the accuracy of the system.

15. Noise

It has been frequently reported in the literature that adding noise to the data that is provided to a neural network can improve the neural network accuracy by leading to better generalization and away from memorization. However, the training of the network in the presence of thermal gradients has been shown to substantially eliminate the need to artificially add noise to the data. Nevertheless, in some cases, improvements have been observed when random arbitrary noise of a rather low level is superimposed on the training data.

16. Photographic Recording of the Setup

After all of the data has been collected and used to train a neural network, it is common to find a significant number of vectors which, when analyzed by the neural network, give a weak or wrong decision. These vectors must be carefully studied especially in comparison with adjacent vectors to see if there is an identifiable cause for the weak or wrong decision. Perhaps the occupant was on the borderline of the keep out zone and strayed into the keep out zone during a particular data collection event. For this reason, it is desirable to photograph each setup simultaneous with the collection of the data. This can be done using a camera mounted in a position whereby it obtains a good view of the seat occupancy. Sometimes several cameras are necessary to minimize the effects of blockage by a newspaper, for example. Having the photographic record of the data setup is also useful when similar results are obtained when the vehicle is subjected to road testing. During road testing, the camera is also present and the test engineer is required to initiate data collection whenever the system does not provide the correct response. The vector and the photograph of this real world test can later be compared to similar setups in the laboratory to see whether there is data that was missed in deriving the matrix of vehicle setups for training the vehicle.

17. Automation

When collecting data in the vehicle it is desirable to automate the motion of the vehicle seat, seatback, windows, visors etc. in this manner the positions of these items can be controlled and distributed as desired by the system designer. This minimizes the possibility of taking too much data at one configuration and thereby unbalancing the network.

18. Automatic Setup Parameter Recording

To achieve an accurate data set, the key parameters of the setup should be recorded automatically. These include the temperatures at various positions inside the vehicle, the position of the vehicle seat, and seatback, the position of the headrest, visor and windows and, where possible, the position of the vehicle occupants. The automatic recordation of these parameters minimizes the effects of human errors.

19. Laser Pointers

During the initial data collection with full horns mounted on the surface of the passenger compartment, care must the exercised so that the transducers are not accidentally moved during the data collection process. In order to check for this possibility, a small laser diode is incorporated into each transducer holder. The laser is aimed so that it illuminates some other surface of the passenger compartment at a known location. Prior to each data taking session, each of the transducer aiming points is checked.

20. Multi-frequency Transducer Placement

When data is collected for dynamic out-of-position, each of the ultrasonic transducers must operate at the different frequency so that all transducers can transmit simultaneously. By this method data can be collected every 10 milliseconds, which is sufficiently fast to approximately track the motion of an occupant during pre-crash braking prior to an impact. A problem arises in the spacing of the frequencies between the different transducers. If the spacing is too close, it becomes very difficult to separate the signals from different transducers and it also affects the sampling rate of the transducer data and thus the resolution of the transducers. If an ultrasonic transducer operates module below 35 kHz it can be sensed by dogs and other animals. If the transducer operates much above 70 kHz, it is very difficult to make the open type of ultrasonic transducer which produces the highest sound pressure. If the multiple

frequency system is used for both the driver and passenger-side, eight separate frequencies are required. In order to find eight frequencies between 35 and 70 kHz, a frequency spacing of 5 kHz is required. In order to use conventional electronic filters and to provide sufficient spacing to permit the desired resolution at the keep out zone border, a 10 kHz spacing is desired. These incompatible requirements can be solved through a careful judicious placement of the transducers such that transducers that are within 5 kHz of each other are placed in such a manner that there is no direct path between the transducers and any indirect path is sufficiently long so that it can be filtered temporarily. An example of such an arrangement is shown on FIG. 11. For this example the transducers operate at the following frequencies A 65 kHz, B 55 kHz, C 35 kHz, D 45 kHz, E 50 kHz, F 40 kHz, G 60 kHz, H 70 kHz. Actually other arrangements adhering to the principle described above would also work.

21. Use of a PC in Data Collection

When collecting data for the training, independent, and validation databases, it is frequently desirable to test the data using various screening techniques and to display the data on a monitor. Thus, during data collection the process is usually monitored using a desktop PC for data taken in the laboratory and a laptop PC for data taken on the road.

22. Use of Referencing Markers and Gages

In addition to and sometimes as a substitution for, the automatic recording of the positions of the seats, seatbacks, windows etc. as described above, a variety of visual markings and gages are frequently used. This includes markings to show the angular position of the seatback, the location of the seat on the seat track, the openness of the window, etc.. Also in those cases where automatic tracking of the occupant is not implemented, visual markings are placed such that a technician can observe that the test occupant remains within the required zone for the particular data taking exercise. Sometimes, a laser diode is used to create a visual line in the space that represents the boundary of the keep out zone or other desired zone boundary.

It is important to realize that the adaptation process described herein applies to any combination of transducers that provide information about the vehicle occupancy. These include weight sensors, capacitive sensors, inductive sensors, moisture sensors, ultrasonic, optic, infrared, radar among others. The adaptation process begins with a selection of candidate transducers for a particular vehicle model. This selection is based on such considerations as cost, alternate uses of the system other than occupant sensing, vehicle interior passenger compartment geometry, desired accuracy and reliability, vehicle aesthetics, vehicle manufacturer preferences, and others. Once a candidate set of transducers has been chosen, these transducers are mounted in the test vehicle according to the teachings of this invention. The vehicle is then subjected to an extensive data collection process wherein various objects are placed in the vehicle at various locations as described below and an initial data set is collected. A pattern recognition system is then developed using the acquired data and an accuracy assessment is made. Further studies are made to determine which, if any, of the transducers can be eliminated from the design. In general the design process begins with a surplus of sensors plus an objective as to how many sensors are to be in the final vehicle installation. The adaptation process can determine which of the transducers are most important and which are least important and the least important transducers can be eliminated to reduce system cost and complexity.

Although several preferred methods are illustrated and described above, there are other possible combinations using

different sensors located at different positions within the automobile passenger compartment which measure either the same or different characteristics of an occupying object to accomplish the same or similar goals as those described herein. There are also numerous additional applications in addition to those described above including, but not limited to, monitoring the driver seat, the center seat or the rear seat of the vehicle or for controlling other vehicle systems in addition to the airbag system. This invention is not limited to the above embodiments and should be determined by the following claims.

APPENDIX 2

Analysis of Neural Network Training and Data Preprocessing Methods—An Example

1. Introduction

The Artificial Neural Network that forms the "brains" of the Occupant Spatial Sensor needs to be trained to recognize airbag enable and disable patterns. The most important part of this training is the data that is collected in the vehicle, which provides the patterns corresponding to these respective configurations. Manipulation of this data (such as filtering) is appropriate if this enhances the information contained in the data. Important too, are the basic network architecture and training methods applied, as these two determine the learning and generalization capabilities of the neural network. The ultimate test for all methods and filters is their effect on the network performance against real world situations.

The Occupant Spatial Sensor (OSS) uses an artificial neural network (ANN) to recognize patterns that it has been trained to identify as either airbag enable or airbag disable conditions. The pattern is obtained from four ultrasonic transducers that cover the front passenger seating area. This pattern consists of the ultrasonic echoes from the objects in the passenger seat area. The signal from each of the four transducers consists of the electrical image of the return echoes, Which is processed by the electronics. The electronic processing comprises amplification (logarithmic compression), rectification, and demodulation (band pass filtering), followed by discretization (sampling) and digitization of the signal. The only software processing required, before this signal can be fed into the artificial neural network, is normalization (i.e. mapping the input to numbers between 0 and 1). Although this is a fair amount of processing, the resulting signal is still considered "raw", because all information is treated equally.

It is possible to apply one or more software preprocessing filters to the raw signal before it is fed into the artificial neural network. The purpose of such filters is to enhance the useful information going into the ANN, in order to increase the system performance. This document describes several preprocessing filters that were applied to the ANN training of a particular vehicle.

2. Data Description

The performance of the artificial neural network is dependent on the data that is used to train the network. The amount of data and the distribution of the data within the realm of possibilities are known to have a large effect on the ability of the network to recognize patterns and to generalize. Data for the OSS is made up of vectors. Each vector is a combination of the useful parts of the signals collected from four ultrasonic transducers. A typical vector could comprise on the order of 100 data points, each representing the (time displaced) echo level as recorded by the ultrasonic transducers.

Three different sets of data are collected. The first set, the training data, contains the patterns that the ANN is being

trained on to recognize as either an airbag deploy or non-deploy scenario. The second set is the independent test data. This set is used during the network training to direct the optimization of the network weights. The third set is the validation (or real world) data. This set is used to quantify the success rate (or performance) of the finalized artificial neural network.

Table 1 shows the main characteristics of these three data sets, as collected for the vehicle. Three numbers characterize the sets. The number of configurations characterizes how many different subjects and objects were used. The number of setups is the product of the number of configurations and the number of vehicle interior variations (seat position and recline, roof and window state, etc.) performed for each configuration. The total number of vectors is then made up of the product of the number of setups and the number of patterns collected while the subject or object moves within the passenger volume.

TABLE 1

Characteristics of the Data Sets

Data Set	Configurations	Setups	Vectors
Training	130	1300	650,000
Independent Test	130	1300	195,000
Validation	100	100	15,000

1.1 Training Data Set Characteristics

The training data set can be split up in various ways into subsets that show the distribution of the data. Table 2 shows the distribution of the training set amongst three classes of passenger seat occupancy: Empty Seat, Human Occupant, and Child Seat. All human occupants were adults of various sizes. No children were part of the training data set other then those seated in Forward Facing Child Seats. Table 3 shows a further breakup of the Child Seats into Forward Facing Child Seats, Rearward Facing Child Seats, Rearward Facing Infant Seats, and out-of-position Forward Facing Child Seats. Table 4 shows a different type of distribution; one based on the environmental conditions inside the vehicle.

TABLE 2

Distribution of Main Training Subjects

Occupancy	Representation
Empty Seat	10%
Human Occupant	32%
Child Seat	58%

TABLE 3

Child Seat Distribution

Child Seat Configuration	Representation
Forward Facing Child Seat	40%
Forward Facing Child Seat Out-of-Position	4%
Rearward Facing Child Seat	27%
Rearward Facing Infant Seat	29%

TABLE 4

Distribution of Environmental Conditions

Environmental Condition	Representation
Ambient	56%
Static Heat (Solar Lamp)	25%
Dynamic Heat (Car Heat)	13%
Dynamic Cooling (Car A C)	6%

1.2 Independent Test Data Characteristics

The independent test data is created using the same configurations, subjects, objects, and conditions as used for the training data set. Its makeup and distributions are therefore the same as those of the training data set.

1.3 Validation Data Characteristics

The distribution of the validation data set into its main subsets is shown in Table 5. This distribution is close to that of the training data set. However the human occupants comprised both children (12% of total) as well as adults (27% of total). Table 6 shows the distribution of human subjects. Contrary to the training and independent test data sets, data was collected on children ages 3 and 6 that were not seated in a child restraint of any kind. Table 7 shows the distribution of the child seats used. On the other hand, no data was collected on Forward Facing Child Seats that were out-of-position. The child and infant seats used in this data set are different from those used in the training and independent test data sets. The validation data was collected with varying environmental conditions as shown in Table 8.

TABLE 5

Validation Data Distribution

Occupancy	Representation
Empty Seat	8%
Human Occupant	39%
Child Seat	53%

TABLE 6

Human Subject Distribution

Human Occupant	Representation	Normally Seated	Out-of-Position
Child age 3	15%	50%	50%
Child age 6	15%	50%	50%
Adult 5^{th} percentile Female	23%	67%	33%
Adult 50^{th} percentile Male	23%	67%	33%
Adult 95^{th} percentile Male	23%	67%	33%

TABLE 7

Child Seat Distribution

Child Seat Configuration	Representation
Forward Facing Child Seat	11%
Forward Facing Booster Seat	11%
Rearward Facing Child Seat	38%
Rearward Facing Infant Seat	40%

TABLE 8

Distribution of Environmental Conditions	
Environmental Condition	Representation
Ambient	63%
Static Heat (Solar Lamp)	13%
Dynamic Heat (Car Heat)	12%
Dynamic Cooling (Car Air Conditioner)	12%

3. Network Training

The baseline network consisted of a four layer back-propagation network with 117 input layer nodes. 20 and 7 nodes respectively in the two hidden layers, and 1 output layer node. The input layer is made up of inputs from four ultrasonic transducers. These were located in the vehicle on the rear quarter panel (A), the A-pillar (B), and the over-head console (C, H). Table 9 shows the number of points, taken from each of these channels that make up one vector.

TABLE 9

Transducer Volume						
	Starting Point			End Point		
Transducer	Sample	Time (ms)	Distance (mm)	Sample	Time (ms)	Distance (mm)
A	5	0.83	142	29	4.84	822
B	3	0.50	85	35	5.84	992
C	7	1.17	198	34	5.67	964
H	2	0.33	57	32	5.34	907

The artificial neural network is implemented using the NeuralWorks Professional II/Plus software. The method used for training the decision mathematical model was back-propagation with Extended Delta-Bar-Delta learning rule and sigmoid transfer function. The Extended DBD paradigm uses past values of the gradient to infer the local curvature of the error surface. This leads to a learning rule in which every connection has a different learning rate and a different momentum term, both of which are automatically calculated.

The network was trained using the above-described training and independent test data sets. An optimum (against the independent test set) was found after 3,675,000 training cycles. Each training cycle uses 30 vectors (known as the epoch), randomly, chosen from the 650,000 available training set vectors. Table 10 shows the performance of the baseline network.

TABLE 10

Baseline Network Performance	
Self Test Success Rate	95.3%
Independent Test Success Rate	94.5%
Validation Test Success Rate	92.7%

The network performance has been further analyzed by investigating the success rates against subsets of the independent test set. The success rate against the airbag enable conditions at 94.6% is virtually equal to that against the airbag disable conditions at 94.4%. Table 11 shows the success rates for the various occupancy subsets. Table 12 shows the success rates for the environmental conditions subsets. Although the distribution of this data was not entirely balanced throughout the matrix, it can be concluded that the system performance is not significantly degraded by heat sources.

TABLE 11

Performance per Occupancy Subset	
Occupancy	Independent Test
Empty Seat	96.1%
Normally Seated Adult	92.1%
Rearward Facing Child/Infant Seat	94.1%
Forward Facing Child Seat	96.9%
Out-of-Position Human/FFCS	93.0%

TABLE 12

Performance per Environmental Conditions Subset	
Environmental Condition	Independent Test
Ambient	95.4%
Long Term Heat (Lamp Heat)	95.2%
Sort Term Heating/Cooling (HVAC)	93.5%

3.1 Normalization

Normalization is used to scale the real world data range into a range acceptable for the network training. The NeuralWorks software requires the use of a scaling factor to bring the input data into a range of 0 to 1, inclusive. Several normalization methods have been explored for their effect on the system performance.

The real world data consists of 12 bit, digitized signals with values between 0 and 4095. FIG. 12 shows a typical raw signal. A raw vector consists of combined sections of four signals.

The results of the normalization study are summarized in Table 13.

TABLE 13

Normalization Study Results			
Normalization Method	Self Test	Independent Test	Validation Test
a. Whole Vector (base)	95.3%	94.5%	92.7%
b. Per Channel	94.9%	93.8%	90.3%
c. Fixed Range [0,4095]	95.6%	90.3%	88.3%

A higher performance results from normalizing across the entire vector versus normalizing per channel. This can be explained from the fact that the baseline method retains the information contained in the relative strength of the signal from one transducer compared to another. This information is lost when using the second method.

Normalization using a fixed range retains the information contained in the relative strength of one vector compared to the next. From this it could be expected that the performance of the network trained with fixed range normalization would increase over that of the baseline method. However, without normalization, the input range is, as a rule, not from zero to the maximum value (see FIG. 1). The absolute value of the data at the input layer affects the network weight adjustment (see equations [1] and [2]). During network training, vectors with a smaller input range will affect the weights calculated for each processing element (neuron) differently than vectors that do span the full range.

$$\Delta w_{ij}^{[s]} = lcoef \cdot e_j^{[s]} \cdot x_i^{[s-1]} \quad [1]$$

$$e_j^{[s]} = x_j^{[s]} \cdot (1.0 - x_j^{[s]}) \cdot \Delta_k (e_k^{[s+1]} \cdot w_{kj}^{[s+1]}) \quad [2]$$

$\Delta w_{ij}^{[s]}$ is the change in the network weights; lcoef is the learning coefficient, $e_j^{[s]}$ is the local error at neuron j in layer s; $x_j^{[s]}$ is the current output state of neuron j in layer s. Variations in the highest and lowest values in the input layer, therefore, have a negative effect on the training of the network. This is reflected in a lower performance against the validation data set.

A secondary effect of normalization is that it increases the resolution of the signal by stretching it out over the full range of 0 to 1, inclusive. As the network predominantly learns from higher peaks in the signal, this results in better generalization capabilities and therefore in a higher performance.

It must be concluded that the effects of the fixed range of input values and the increased resolution resulting from the baseline normalization method have a stronger effect on the network training than retaining the information contained in the relative vector strength.

3.2 Low Threshold Filters

Not all information contained in the raw signals can be considered useful for network training. Low amplitude echoes are received back from objects on the outskirts of the ultrasonic field that should not be included in the training data. Moreover, low amplitude noise, from various sources, is contained within the signal. This noise shows up strongest where the signal is weak. By using a low threshold filter, the signal to noise ratio of the vectors can be improved before they are used for network training.

Three cutoff levels were used: 5%, 10%, and 20% of the signal maximum value (4095). The method used, brings the values below the threshold up to the threshold level. Subsequent vector normalization (baseline method) stretches the signal to the full range of [0,1].

The results of the low threshold filter study are summarized in Table 14.

TABLE 14

Low Threshold Filter Study Results

Threshold Level	Self Test	Independent Test	Validation Test
none (base)	95.3%	94.5%	92.7%
5% of 4095	95.3%	94.4%	91.9%
10% of 4095	95.3%	94.3%	92.5%
20% of 4095	95.1%	94.2%	86.4%

The performance of the networks trained with 5% and 10% threshold filter is similar to that of the baseline network. A small performance degradation is observed for the network trained with a 20% threshold filter. From this it is concluded that the noise level is sufficiently low to not affect the network training. At the same time it can be concluded that the lower 10% of the signal can be discarded without affecting the network performance. This allows the definition of demarcation lines on the outskirts of the ultrasonic field where the signal is equal to 10% of the maximum field strength.

4. Network Types

The baseline network is a back-propagation type network. Back-propagation is a general-purpose network paradigm that has been successfully used for prediction, classification, system modeling, and filtering as well as many other general types of problems. Back propagation learns by calculating an error between desired and actual output and propagating this error information back to each node in the network. This back-propagate error is used to drive the learning at each node. Some of the advantages of a back-propagation network are that it attempts to minimize the global error and that it can provide a very compact distributed representation of complex data sets. Some of the disadvantages are its slow learning and the irregular boundaries and unexpected classification regions due to the distributed nature of the network and the use of a transfer functions that is unbounded. Some of these disadvantages can be overcome by using a modified back-propagation method such as the Extended Delta-Bar-Delta paradigm. The EDBD algorithm automatically calculates the learning rate and momentum for each connection in the network, which facilitates optimization of the network training.

Many other network architectures exist that have different characteristics than the baseline network. One of these is the Logicon Projection Network. This type of network combines the advantages of closed boundary networks with those of open boundary networks (to which the back-propagation network belongs). Closed boundary networks are fast learning because they can immediately place prototypes at the input data points and match all input data to these prototypes. Open boundary networks, on the other hand, have the capability to minimize the output error through gradient decent.

Conclusions

The baseline artificial neural network trained to a success rate of 92.7% against the validation data set. This network has a four-layer back-propagation architecture and uses the Extended Delta-Bar-Delta learning rule and sigmoid transfer function. Pre-processing comprised vector normalization while post-processing comprised a "five consistent decision" filter.

The objects and subjects used for the independent test data were the same as those used for the training data. This may have negatively affected the network's classification generalization abilities.

The spatial distribution of the independent test data was as wide as that of the training data. This as resulted in a network that can generalize across a large spatial volume. A lighter performance across a smaller volume, located immediately around the peak of the normal distribution, combined with a lower performance on the outskirts of the distribution curve, might be preferable.

To achieve this, the distribution of the independent test set needs to be a reflection of the normal distribution for the system (a.k.a. native population).

Modifying the pre-processing method or applying additional pre-processing methods did not show a significant improvement of the performance over that of the baseline network. The baseline normalization method gave the best results as it improves the learning by keeping the input values in a fixed range and increases the signal resolution. The lower threshold study showed that the network learns from the larger peaks in the echo pattern. Pre-processing techniques should be aimed at increasing the signal resolution to bring out these peaks.

A further study could be performed to investigate combining a lower threshold with fixed range normalization, using a range less than full scale. This would force each vector to include at least one point at the lower threshold value and one value in saturation effectively forcing each vector into a fixed range that can be mapped between 0 and 1, inclusive. This would have the positive effects associated with the baseline normalization, while retaining the information contained in the relative vector strength. Raw vectors points that, as a result of the scaling, would fall outside the range of 0 to 1 would then be mapped to 0 and 1 respectively.

Post-processing should be used to enhance the network recognition ability with a memory function. The possibilities

for such are currently frustrated by the necessity, of one network performing both object classification as well as spatial locating functions. Performing the spatial locating function requires flexibility to rapidly update the system status. Object classification, on the other hand, benefits from decision rigidity to nullify the effect of an occasional pattern that is incorrectly classified by the network

APPENDIX 3

Process For Training an OPS System DROOP Network For a Specific Vehicle

1. Define customer requirements and deliverable
   1.1. Number of zones
   1.2. Number of outputs
   1.3. At risk zone definition
   1.4. Decision definition i.e. empty seat at risk, safe seating, or not critical and undetermined
   1.5. Determine speed of DROOP decision
2. Develop PERT chart for the program
3. Determine viable locations for the transducer mounts
   3.1. Manufacturability
   3.2. Repeatability
   3.3. Exposure (not able to damage during vehicle life)
4. Evaluate location of mount logistics
   4.1. Field dimensions
   4.2. Multipath reflections
   4.3. Transducer Aim
   4.4. Obstructions/Unwanted data
   4.5. Objective of view
   4.6. Primary DROOP transducers requirements
5. Develop documentation logs for the program (vehicle books)
6. Determine vehicle training variables
   6.1. Seat track stops
   6.2. Steering wheel stops
   6.3. Seat back angles
   6.4. DROOP transducer blockage during crash
   6.5. Etc . . .
7. Determine and mark at risk zone in vehicle
8. Evaluate location physical impediments
   8.1. Room to mount/hide transducers
   8.2. Sufficient hard mounting surfaces
   8.3. Obstructions
9. Develop matrix for training, independent, validation, and DROOP data sets
10. Determine necessary equipment needed for data collection
    10.1. Child/booster/infant seats
    10.2. Maps/razors/makeup
    10.3. Etc . . .
11. Schedule sled tests for initial and final DROOP networks
12. Design test buck for DROOP
13. Design test dummy for DROOP testing
14. Purchase any necessary variables
    14.1. Child/booster/infant seats
    14.2. Maps/razors/makeup
    14.3. Etc . . .
15. Develop automated controls of vehicle accessories
    15.1. Automatic seat control for variable empty seat
    15.2. Automatic seat back angle control for variable empty seat
    15.3. Automatic window control for variable empty seat
    15.4. Etc . . .
16. Acquire equipment to build automated controls
17. Build & install automated controls of vehicle variables
18. Install data collection aides
    18.1. Thermometers
    18.2. Seat track gauge
    18.3. Seat angle gauge
    18.4. Etc . . .
19. Install switched and fused wiring for:
    19.1. Transducer pairs
    19.2. Lasers
    19.3. Decision Indicator Lights
    19.4. System box
    19.5. Monitor
    19.6. Power automated control items
    19.7. Thermometers, potentiometers
    19.8. DROOP occupant ranging device
    19.9. DROOP ranging indicator
    19.10. Etc . . .
20. Write DROOP operating software for OPS system box
21. Validate DROOP operating software for OPS
22. Build OPS system control box for the vehicle with special DROOP operating software
23. Validate & document system control box
24. Write vehicle specific DROOP data collection software (pollbin)
25. Write vehicle specific DROOP data evaluation program (picgraph)
26. Evaluate DROOP data collection software
27. Evaluate DROOP data evaluation software
28. Load DROOP data collection software on OPS system box and validate
29. Load DROOP data evaluation software on OPS system box and validate
30. Train technicians on DROOP data collection techniques and use of data collection software
31. Design prototype mounts based on known transducer variables
32. Prototype mounts
33. Pre-build mounts
    33.1. Install transducers in mounts
    33.2. Optimize to eliminate crosstalk
    33.3. Obtain desired field
    33.4. Validate performance of DROOP requirements for mounts
34. Document mounts
    34.1. Polar plots of fields
    34.2. Drawings with all mount dimensions
    34.3. Drawings of transducer location in the mount
35. Install mounts in the vehicle
36. Map fields in the vehicle using ATI designed apparatus and specification
37. Map performance in the vehicle of the DROOP transducer assembly
38. Determine sensor volume
39. Document vehicle mounted transducers and fields
    39.1. Mapping per ATI specification
    39.2. Photographs of all fields
    39.3. Drawing and dimensions of installed mounts
    39.4. Document sensor volume
    39.5. Drawing and dimensions of aim & field
40. Using data collection software and OPS system box collect initial 16 sheets of training, independent, and validation data
41. Determine initial conditions for training the ANN
    41.1. Normalization method
    41.2. Training via back propagation or ?
    41.3. Weights
    41.4. Etc . . .
42. Pre-process data
43. Train an ANN on above data

44. Develop post processing strategy if necessary
45. Develop post processing software
46. Evaluate ANN with validation data and in vehicle analysis
47. Perform sled tests to confirm initial DROOP results
48. Document DROOP testing results and performance
49. Rework mounts and repeat steps 31 through 48 if necessary
50. Meet with customer and review program
51. Develop strategy for customer directed outputs
  51.1. Develop strategy for final ANN multiple decision networks if necessary
  51.2. Develop strategy for final ANN multiple layer networks if necessary
  51.3. Develop strategy for DROOP layer/network
52. Design daily calibration jig
53. Build daily calibration jig
54. Develop daily calibration test
55. Document daily calibration test procedure & jig
56. Collect daily calibration tests
57. Document daily calibration test results
58. Rework vehicle data collection markings for customer directed outputs
  58.1. Multiple zone identifiers for data collection
59. Schedule subjects for all data sets
60. Train subjects for data collection procedures
61. Using DROOP data collection software and OPS system box collect initial 16 sheets of training, independent, and validation data
62. Collect total amount of vectors deemed necessary by program directives, amount will vary as outputs and complexity of ANN varies
63. Determine initial conditions for training the ANN
  63.1. Normalization method
  63.2. Training via back propagation or ?
  63.3. Weights
  63.4. Etc . . .
64. Pre-process data
65. Train an ANN on above data
66. Develop post processing strategy
  66.1. Weighting
  66.2. Averaging
  66.3. Etc . . .
67. Develop post processing software
68. Evaluate ANN with validation data
69. Perform in vehicle hole searching and analysis
70. Perform in vehicle non sled mounted DROOP tests
71. Determines need for further training or processing
72. Repeat steps 58 through 71 if necessary
73. Perform sled tests to confirm initial DROOP results
74. Document DROOP testing results and performance
75. Repeat steps 58 through 74 if necessary
76. Write summary performance report
77. Presentation of vehicle to the customer
78. Delivered an OPS equipped vehicle to the customer

Appendix 1

Subject Classification

Class	Instances	Weight Category	State
ES	Empty Seat	< 10 lb	Empty
FFA	Normally Seated Adult	> 105 lb	Enable
FFC	Normally Seated Child	<10,105> lb	Enable
FFC	Normally Positioned Forward Facing Child Seat	<10,45> lb	Enable
OOP	Out-of-position Adult	> 105 lb	Disable
OOP	Out-of-position Child	< 105 lb	Disable
OOP	Out-of-position Forward Facing Child Seat	<10,45> lb	Disable
RFS	Rearward Facing Child Seat	<10,45> lb	Disable
RFS	Rearward Facing Infant Seat	<10,45> lb	Disable

Categorization of Human Subjects

	Weight Range kg (lb)	Height Range m (in)		
Child		<0.95,1.15> (<3'1",3'9">)	<1.10,1.30> (<3'7",4'3">)	<1.25,1.45> (<4'1",4'9">)
	<11,25> (<24,55>)	C11	C12	C13
	<22,36> (<48,79>)	C21	C22	C23
	<33,47> (<73,103>)	C31	C32	C33
Adult		<1.45,1.65> (<4'9",5'5">)	<1.60,1.80> (<5'3",5'11">)	<1.75,1.95> (<5'9",6'5">)
	<45,70> (<99,154>)	A11	A12	A13
	<65,90> (<143,198>)	A21	A22	A23
	<85,110> (<187,242>)	A31	A32	A33

All Human Subjects are to wear light clothes (typically slacks and T-shirt) on entry. Other types of clothing to be provided by ATI

Child Surrogates

Doll		Baby = 0.50 m (approx. 20")	Infant = 0.75 m (approx. 30")	Child = 1.20 m (approx. 48")

Rearward Facing Infant Seats

Designation	Child Seat	Attributes
Training	Arriva	base, hood
Independent	Assura 565	hood
Training	Baby-Safe	-
Training	Century 590	base, hood
Training	Evenflo Discovery	base, Tbar
Training	Evenflo Joyride (new)	hood
Independent	Evenflo Joyride (old)	-
Training	Gerry Guard	base
Validation	Kolcraft Travelabout	base, Tbar
Training	Rock-n-Ride	-
Training	TLC	-

Rearward Facing Child Seat

Designation	Child Seat	Attributes
Training	Century 1000	-
Validation	Century 2000 STE	-
Training	Century Ovation	-
Training	Century Smartmove 5T	table
Training	Champion	table
Training	Fisher Price Child Seat	table
Training	Touriva	-
Training	Ultara	table
Training	Vario Exclusive	table

Forward Facing Child and Booster Seats

Designation	Child Seat	Attributes
Training	Century 1000	-
Validation	Century 2000 STE	-
Training	Century Ovation	-
Validation	Century Smartmove 5T	table
Training	Champion	table
Validation	Fisher Price Booster	-
Training	Fisher Price Child Seat	table
Training	Gerry Booster	table
Training	Touriva	-
Training	Ultara	table
Training	Vario Exclusiv	table

Vehicle Configuration Series

Configuration	Seat Track (+/- 0.5")										Seatback Recline (+/- 2°)									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
A	0	0	2	2	2	4	4	6	6	6	0	18	4	12	20	2	20	0	8	16
B	1	1	3	3	3	5	5	7	7	7	2	20	0	8	16	0	18	4	12	20
C	0	0	2	2	4	4	4	6	6	8	5	15	4	16	0	15	20	2	10	18
D	1	1	3	3	5	5	5	7	7	7	4	16	5	15	2	10	18	0	15	20
E	0	0	0	2	2	2	4	4	6	8	0	8	16	4	12	20	2	20	0	18
F	1	1	1	3	3	3	5	5	7	7	4	12	20	0	8	16	0	18	2	20
G	0	0	2	2	2	4	4	4	6	8	4	16	2	20	2	10	18	0	15	20
H	1	1	3	3	3	5	5	5	7	7	2	20	4	16	0	15	20	2	10	18

Configuration	Windows										Visor										Convertible Top									
	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
A	D	D	U	U	D	D	U	U	D	D	U	D	U	D	S	U	D	U	D	S	U	U	U	U	U	D	D	D	D	D
B	U	U	D	D	U	U	D	D	U	U	D	U	D	U	S	D	U	D	U	S	D	D	D	D	D	U	U	U	U	U
C	U	U	D	D	U	U	D	D	U	U	U	D	S	U	D	U	D	S	U	D	D	D	D	D	D	U	U	U	U	U
D	D	D	U	U	D	D	U	U	D	D	D	U	S	D	U	D	U	S	D	U	U	U	U	U	U	D	D	D	D	D
E	D	D	U	U	D	D	U	U	D	D	D	U	D	S	U	D	U	S	D	U	U	U	U	U	U	D	D	D	D	D
F	U	U	D	D	U	U	D	D	U	U	U	D	U	S	D	U	D	S	U	D	D	D	D	D	D	U	U	U	U	U
G	U	U	D	D	U	U	D	D	U	U	U	S	D	U	D	U	D	U	S	D	D	D	D	D	D	U	U	U	U	U
H	D	D	U	U	D	D	U	U	D	D	D	S	U	D	U	D	U	D	S	U	U	U	U	U	U	D	D	D	D	D

Sequence for Child Seat Training Data Collection:

- Start object in center of the seat. Trainer has both hands on the steering wheel;
- With a smooth motion, push the object fully outboard, then pull it fully inboard, then push it to center position, then put hands back on the steering wheel;
- With a smooth motion, rotate the object 45 degrees outboard, the rotate 45 degrees inboard, then rotate back to center, then put hands back on the wheel.

Sequence for Out-of-Position Forward Facing Child Seat Training Data Collection

- Start with object in the center line, leaning onto the Instrument Panel;
- With a smooth motion, push the object fully outboard, then pull it fully inboard, then push it to the center;
- Repeat this sequence with a 150 mm (6") gap between the object and the Instrument Panel; Apply small (+/- 10°) rotations.
- Repeat this sequence with a 300 mm (12") gap between the object and the Instrument Panel; Apply small (+/- 10°) rotations.

Sequence for Human Subject Training Data Collection:

- Lean forward and outboard such that head and/or shoulders touch the Fire line;
- Gently traverse inboard while carefully following the Fire line until the center of the vehicle is reached;
- Lean halfway back towards the seatback and traverse outboard up against the side window. Rotate torso while doing so;
- Lean back into the seat and traverse inboard towards the center. Rotate torso while doing so;
- Sit back in the seat; "operate" radio controls, glove box, window, or seat controls; assume a brace posture;
- Do *not* cross the Fire line with head and/or shoulders at any time.

Sequence for Out-of-Position Human Subject Training Data Collection:

- Lean forward and outboard such that head and/or shoulders touch the Instrument Panel;
- Gently traverse inboard towards the center console;
- Move back 150 mm (6") and gently traverse back to the most outboard position;
- Move back 300 mm (12") and gently traverse back to the center console;
- "Operate" radio controls and glovebox while head and/or shoulders remain in front of the Fire line.

Network Training Set Collection Matrix (Vehicle E)
Rev 1.1

#	Class	Subject/Object	Attributes	Actions	Config.	Belt	Conditions
1	ES	None	None	Motions of track and recline	(A)	N.A.	Ambient
2	FFA	A22	Medium Clothes, Magazine	Motions in safe seating area	B	Yes	Ambient
3	OOP	A22	Medium Clothes	Motions in NFZ	C	No	Ambient
4	FFC	Century 1000	Infant Doll	Motions in safe seating area	D	No	Ambient
5	RFS	Century 1000	Baby Doll	Motions in entire seating area	E	No	Ambient
6	ES	None	Beaded Cover	Motions of track and recline	(F)	N.A.	Ambient
7	FFA	A11	Medium Clothes	Motions in safe seating area	G	Yes	Ambient
8	OOP	Touriva	Infant Doll, Blanket	Motions in NFZ	H	No	Ambient
9	FFC	Touriva	Infant Doll, Blanket	Motions in safe seating area	A	No	Ambient
10	RFS	Century 590	Baby Doll, Hood	Motions in entire seating area	B	No	Ambient
11	ES	None	Fabric Cover	Motions of track and recline	(C)	N.A.	Ambient
12	FFA	A33	Medium Clothes, Newspaper	Motions in safe seating area	D	No	Ambient
13	OOP	A33	Medium Clothes	Motions in NFZ	E	Yes	Ambient
14	FFC	C22	Medium Clothes	Motions in safe seating area	F	No	Ambient
15	RFS	Touriva	Baby Doll, Blanket	Motions in entire seating area	G	No	Ambient
16	ES	None	Blanket	Motions of track and recline	(H)	N.A.	Ambient
17	FFA	A21	Heavy Clothes	Motions in safe seating area	A	No	Ambient
18	OOP	C11	Heavy Clothes	Motions in NFZ (standing)	B	No	Ambient
19	FFC	C11	Heavy Clothes	Motions in safe seating area	C	No	Ambient
20	RFS	TLC	Baby Doll	Motions in entire seating area	D	No	Ambient
21	ES	None	None	Motions of track and recline	(E)	N.A.	Solar Heat
22	FFA	A12	Light Clothes, Magazine	Motions in safe seating area	F	Yes	Solar Heat
23	OOP	A12	Light Clothes	Motions in NFZ	G	No	Solar Heat
24	FFC	Champion	Infant Doll	Motions in safe seating area	H	No	Solar Heat

25	RFS	Champion	Baby Doll	Motions in entire seating area	A	No	Solar Heat
26	ES	None	Beaded Cover	Motions of track and recline	(B)	N.A.	Solar Heat
27	FFA	A23	Light Clothes	Motions in safe seating area	C	Yes	Solar Heat
28	OOP	Vario Exclusive	Child Doll	Motions in NFZ	D	No	Solar Heat
29	FFC	Vario Exclusive	Child Doll, Blanket	Motions in safe seating area	E	No	Solar Heat
30	RFS	Joyride (new)	Baby Doll	Motions in entire seating area	F	No	Solar Heat
31	ES	None	Fabric Cover	Motions of track and recline	(G)	N.A.	Solar Heat
32	FFA	A32	Light Clothes, Newspaper	Motions in safe seating area	H	No	Solar Heat
33	OOP	A32	Light Clothes	Motions in NFZ	A	Yes	Solar Heat
34	FFC	C33	Light Clothes	Motions in safe seating area	B	No	Solar Heat
35	RFS	Ultara	Baby Doll, Blanket	Motions in entire seating area	C	No	Solar Heat
36	ES	None	Blanket	Motions of track and recline	(D)	N.A.	Solar Heat
37	FFA	A22	Medium Clothes	Motions in safe seating area	E	No	Solar Heat
38	OOP	C21	Medium Clothes	Motions in NFZ	F	No	Solar Heat
39	FFC	C21	Medium Clothes	Motions in safe seating area	G	No	Solar Heat
40	RFS	Arriva	Baby Doll, Hood	Motions in entire seating area	H	No	Solar Heat
41	ES	None	Handbag	Motions of track and recline	(H)	N.A.	Ambient
42	FFA	A11	Heavy Clothes, Magazine	Motions in safe seating area	G	Yes	Ambient
43	OOP	A11	Heavy Clothes	Motions in NFZ	F	No	Ambient
44	FFC	Gerry Booster	Infant Doll	Motions in safe seating area	E	No	Ambient
45	RFS	Fisher Price CS	Baby Doll	Motions in entire seating area	D	No	Ambient
46	ES	None	Beaded Cover, Handbag	Motions of track and recline	(C)	N.A.	Ambient
47	FFA	A33	Heavy Clothes	Motions in safe seating area	B	Yes	Ambient
48	OOP	Ultara	Inflant Doll, Blanket	Motions in NFZ	A	No	Ambient
49	FFC	Ultara	Inflant Doll, Blanket	Motions in safe seating area	H	No	Ambient
50	RFS	Baby Safe	Baby Doll, Handle up	Motions in entire seating area	G	No	Ambient
51	ES	None	Fabric Cover, Handbag	Motions of track and recline	(F)	N.A.	Ambient
52	FFA	A21	Heavy Clothes, Newspaper	Motions in safe seating area	E	No	Ambient
53	OOP	A21	Heavy Clothes	Motions in NFZ	D	Yes	Ambient
54	FFC	C12	Heavy Clothes	Motions in safe seating area	C	No	Ambient

55	RFS	Vario Exclusive	Baby Doll, Blanket	Motions in entire seating area	B	No	Ambient
56	ES	None	Blanket, Handbag	Motions of track and recline	(A)	N.A.	Ambient
57	FFA	A12	Rain Clothes	Motions in safe seating area	H	No	Ambient
58	OOP	C23	Rain Clothes	Motions in NFZ	G	No	Ambient
59	FFC	C23	Rain Clothes	Motions in safe seating area	F	No	Ambient
60	RFS	Rock'n'Ride	Baby Doll	Motions in entire seating area	E	No	Ambient
61	ES	None	None	Motions of track and recline	(D)	N.A.	Air Conditioner
62	FFA	A23	Light Clothes, Magazine	Motions in safe seating area	C	Yes	Air Conditioner
63	OOP	A23	Light Clothes	Motions in NFZ	B	No	Air Conditioner
64	FFC	Century Ovation	Infant Doll	Motions in safe seating area	A	No	Air Conditioner
65	RFS	Century Ovation	Baby Doll	Motions in entire seating area	H	No	Air Conditioner
66	ES	None	Beaded Cover	Motions of track and recline	(G)	N.A.	Air Conditioner
67	FFA	A32	Light Clothes	Motions in safe seating area	F	Yes	Air Conditioner
68	OOP	Fisher Price CS	Child Doll	Motions in NFZ	E	No	Air Conditioner
69	FFC	Fisher Price CS	Child Doll, Blanket	Motions in safe seating area	D	No	Air Conditioner
70	RFS	Gerry Guard	Baby Doll	Motions in entire seating area	C	No	Air Conditioner
71	ES	None	Fabric Cover	Motions of track and recline	(B)	N.A.	Air Conditioner
72	FFA	A22	Light Clothes, Newspaper	Motions in safe seating area	A	No	Air Conditioner
73	OOP	A22	Light Clothes	Motions in NFZ	H	Yes	Air Conditioner
74	FFC	C32	Light Clothes	Motions in safe seating area	G	No	Air Conditioner
75	RFS	Smartmove 5T	Baby Doll, Blanket	Motions in entire seating area	F	No	Air Conditioner
76	ES	None	Blanket	Motions of track and recline	(E)	N.A.	Air Conditioner
77	FFA	A11	Medium Clothes	Motions in safe seating area	D	No	Air Conditioner
78	OOP	C22	Medium Clothes	Motions in NFZ	C	No	Air Conditioner
79	FFC	C22	Medium Clothes	Motions in safe seating area	B	No	Air Conditioner
80	RFS	Discovery	Baby Doll, Handle up	Motions in entire seating area	A	No	Air Conditioner
81	ES	None	Pizza Box	Motions of track and recline	(B)	N.A.	Ambient
82	FFA	A33	Rain Clothes, Magazine	Motions in safe seating area	A	Yes	Ambient
83	OOP	A33	Rain Clothes	Motions in NFZ	D	Yes	Ambient
84	FFC	Champion	Infant Doll	Motions in safe seating area	C	No	Ambient

85	RFS	Champion	Baby Doll	Motions in entire seating area	F	No	Ambient
86	ES	None	Beaded Cover, Pizza Box	Motions of track and recline	(E)	N.A.	Ambient
87	FFA	A21	Rain Clothes	Motions in safe seating area	H	Yes	Ambient
88	OOP	Vario Exclusive	Child Doll, Blanket	Motions in NFZ	G	No	Ambient
89	FFC	Vario Exclusive	Child Doll, Blanket	Motions in safe seating area	B	No	Ambient
90	RFS	Joyride (new)	Baby Doll, Hood	Motions in entire seating area	A	No	Ambient
91	ES	None	Fabric Cover, Pizza Box	Motions of track and recline	(D)	N.A.	Ambient
92	FFA	A12	Rain Clothes, Newspaper	Motions in safe seating area	C	No	Ambient
93	OOP	A12	Rain Clothes	Motions in NFZ	F	No	Ambient
94	FFC	C23	Rain Clothes	Motions in safe seating area	E	No	Ambient
95	RFS	Ultara	Baby Doll, Blanket	Motions in entire seating area	H	No	Ambient
96	ES	None	Blanket, Pizza Box	Motions of track and recline	(G)	N.A.	Ambient
97	FFA	A23	Light Clothes	Motions in safe seating area	B	No	Ambient
98	OOP	C32	Light Clothes	Motions in NFZ	A	No	Ambient
99	FFC	C32	Light Clothes	Motions in safe seating area	D	No	Ambient
100	RFS	Arriva	Baby Doll, Hood	Motions in entire seating area	C	No	Ambient
101	ES	None	None	Motions of track and recline	(F)	N.A.	Car Heat
102	FFA	A32	Light Clothes, Magazine	Motions in safe seating area	E	Yes	Car Heat
103	OOP	A32	Light Clothes	Motions in NFZ	H	Yes	Car Heat
104	FFC	Century 1000	Infant Doll	Motions in safe seating area	G	No	Car Heat
105	RFS	Century 1000	Baby Doll	Motions in entire seating area	B	No	Car Heat
106	ES	None	Beaded Cover	Motions of track and recline	(A)	N.A.	Car Heat
107	FFA	A22	Rain Clothes	Motions in safe seating area	D	Yes	Car Heat
108	OOP	Vario Exclusive	Infant Doll	Motions in NFZ	C	No	Car Heat
109	FFC	Touriva	Infant Doll, Blanket	Motions in safe seating area	F	No	Car Heat
110	RFS	Century 590	Baby Doll	Motions in entire seating area	E	No	Car Heat
111	ES	None	Fabric Cover	Motions of track and recline	(H)	N.A.	Car Heat
112	FFA	A11	Light Clothes, Newspaper	Motions in safe seating area	G	No	Car Heat
113	OOP	A11	Light Clothes	Motions in NFZ	B	No	Car Heat
114	FFC	C32	Light Clothes	Motions in safe seating area	A	No	Car Heat

115	RFS	Touriva	Baby Doll, Blanket	Motions in entire seating area	D	No	Car Heat
116	ES	None	Blanket	Motions of track and recline	(C)	N.A.	Car Heat
117	FFA	A33	Heavy Clothes	Motions in safe seating area	F	No	Car Heat
118	OOP	C22	Heaby Clothes	Motions in NFZ	E	No	Car Heat
119	FFC	C22	Heavy Clothes	Motions in safe seating area	H	No	Car Heat
120	RFS	TLC	Baby Doll	Motions in entire seating area	G	No	Car Heat
121	ES	None	Attaché Case (flat)	Motions of track and recline	(G)	N.A.	Ambient
122	FFA	A21	Heavy Clothes, Magazine	Motions in safe seating area	H	Yes	Ambient
123	OOP	A21	Heavy Clothes	Motions in NFZ	E	Yes	Ambient
124	FFC	Century Ovation	Infant Doll	Motions in safe seating area	F	No	Ambient
125	RFS	Century Ovation	Baby Doll	Motions in entire seating area	C	No	Ambient
126	ES	None	Beaded Cover, Attaché Case	Motions of track and recline	(D)	N.A.	Ambient
127	FFA	A12	Rain Clothes	Motions in safe seating area	A	Yes	Ambient
128	OOP	Fisher Price CS	Inflant Doll, Blanket	Motions in NFZ	B	No	Ambient
129	FFC	Fisher Price CS	Inflant Doll	Motions in safe seating area	G	No	Ambient
130	RFS	Gerry Guard	Baby Doll, Handle up	Motions in entire seating area	H	No	Ambient
131	ES	None	Fabric Cover, Attaché Case	Motions of track and recline	(E)	N.A.	Ambient
132	FFA	A23	Heavy Clothes, Newspaper	Motions in safe seating area	F	No	Ambient
133	OOP	A23	Heavy Clothes	Motions in NFZ	C	No	Ambient
134	FFC	C11	Heavy Clothes	Motions in safe seating area	D	No	Ambient
135	RFS	Smartmove 5T	Baby Doll, Blanket	Motions in entire seating area	A	No	Ambient
136	ES	None	Blanket, Attaché Case	Motions of track and recline	(B)	N.A.	Ambient
137	FFA	A32	Rain Clothes	Motions in safe seating area	G	No	Ambient
138	OOP	C33	Rain Clothes	Motions in NFZ	H	No	Ambient
139	FFC	C33	Rain Clothes	Motions in safe seating area	E	No	Ambient
140	RFS	Discovery	Baby Doll, Handle up	Motions in entire seating area	F	No	Ambient
141	ES	None	Hand Bag	Motions of track and recline	(C)	N.A.	Solar Heat
142	FFA	A22	Medium Clothes, Magazine	Motions in safe seating area	D	Yes	Solar Heat
143	OOP	A22	Heavy Clothes	Motions in NFZ	A	Yes	Solar Heat
144	FFC	Gerry Booster	Child Doll	Motions in safe seating area	B	No	Solar Heat

145	RFS	Fisher Price CS	Baby Doll	Motions in entire seating area	G	No	Solar Heat
146	ES	None	Beaded Cover, Hand Bag	Motions of track and recline	(H)	N.A.	Solar Heat
147	FFA	A11	Medium Clothes	Motions in safe seating area	E	Yes	Solar Heat
148	OOP	Vario Exclusive	Infant Doll	Motions in NFZ	F	No	Solar Heat
149	FFC	Ultara	Infant Doll, Blanket	Motions in safe seating area	C	No	Solar Heat
150	RFS	Baby Safe	Baby Doll	Motions in entire seating area	D	No	Solar Heat
151	ES	None	Fabric Cover, Hand Bag	Motions of track and recline	(A)	N.A.	Solar Heat
152	FFA	A33	Medium Clothes, Newspaper	Motions in safe seating area	B	No	Solar Heat
153	OOP	A33	Medium Clothes	Motions in NFZ	G	No	Solar Heat
154	FFC	C33	Medium Clothes	Motions in safe seating area	H	No	Solar Heat
155	RFS	Vario Exclusive	Baby Doll, Blanket	Motions in entire seating area	E	No	Solar Heat
156	ES	None	Blanket, Hand Bag	Motions of track and recline	(F)	N.A.	Solar Heat
157	FFA	A21	Light Clothes	Motions in safe seating area	C	No	Solar Heat
158	OOP	C21	Light Clothes	Motions in NFZ	D	No	Solar Heat
159	FFC	C21	Light Clothes	Motions in safe seating area	A	No	Solar Heat
160	RFS	Rock'n'Ride	Baby Doll	Motions in entire seating area	B	No	Solar Heat

Network Independent Test Set Collection Matrix (Vehicle E)

Rev 1.1 (Under Construction)

#	Class	Subject/Object	Attributes	Actions	Config.	Belt	Conditions
1	ES			Motions of track and recline	(A)	N.A.	Ambient
2	FFA			Motions in safe seating area	B	Yes	Ambient
3	OOP			Motions in NFZ	C	No	Ambient
4	FFC			Motions in safe seating area	D	No	Ambient
5	RFS			Motions in entire seating area	E	No	Ambient
6	ES			Motions of track and recline	(F)	N.A.	Ambient
7	FFA			Motions in safe seating area	G	Yes	Ambient
8	OOP			Motions in NFZ	H	No	Ambient
9	FFC			Motions in safe seating area	A	No	Ambient
10	RFS			Motions in entire seating area	B	No	Ambient
11	ES			Motions of track and recline	(C)	N.A.	Ambient
12	FFA			Motions in safe seating area	D	No	Ambient
13	OOP			Motions in NFZ	E	Yes	Ambient
14	FFC			Motions in safe seating area	F	No	Ambient
15	RFS			Motions in entire seating area	G	No	Ambient
16	ES			Motions of track and recline	(H)	N.A.	Ambient
17	FFA			Motions in safe seating area	A	No	Ambient
18	OOP			Motions in NFZ (standing)	B	No	Ambient
19	FFC			Motions in safe seating area	C	No	Ambient
20	RFS			Motions in entire seating area	D	No	Ambient

We claim:

1. A system for determining the occupancy state of a seat in a vehicle in combination with the vehicle, the system comprising:

a plurality of transducers arranged in the vehicle, each of said transducers providing data relating to the occupancy state of the seat; and

processor means coupled to said transducers for receiving the data from said transducers and processing the data to obtain an output indicative of the current occupancy state of the seat, said processor means comprising a trained pattern recognition algorithm created from a plurality of data sets, each of said data sets representing a different occupancy state of the seat and being formed from data from said transducers while the seat is in that occupancy state,

said trained pattern recognition algorithm producing the output indicative of the current occupancy state of the seat upon inputting a data set representing the current occupancy state of the seat and being formed from data from said transducers.

2. The vehicle of claim 1, wherein each of said transducers generates only a single stream of data relating to the occupancy state of the seat and said processor means are arranged to accept only the single stream of data from each of said transducers such that the stream of data from each of said transducers is passed to said processor means without combining with another stream of data.

3. The vehicle of claim 1, wherein at least one of said transducers is a reclining angle detecting sensor for detecting a tilt angle of a back portion of the seat.

4. The vehicle of claim 1, wherein one of said transducers is a seat position sensor for detecting the position of the seat relative to a fixed reference point in the vehicle.

5. The vehicle of claim 1, wherein one of said transducers is a heartbeat sensor for sensing a heartbeat of an occupying item of the seat.

6. The vehicle of claim 1, wherein said transducers include a plurality of weight sensors, each of said weight sensors measuring the weight applied onto the seat at a different location.

7. The vehicle of claim 1, wherein said transducers include a weight sensor arranged to measure the weight applied to a surface of a seat portion of the seat.

8. The vehicle of claim 1, wherein said transducers include a force, pressure or strain gage arranged to measure the weight applied to the entire seat.

9. The vehicle of claim 8, wherein the seat includes a support structure for supporting the seat above a floor of a passenger compartment of the vehicle, said force, pressure or strain gage being attached to the support structure.

10. The vehicle of claim 1, wherein said transducers include a plurality of electromagnetic wave sensors capable of receiving waves at least from a space above the seat, each of said electromagnetic wave sensors being arranged at a different location.

11. The vehicle of claim 1, wherein said transducers include at least two ultrasonic sensors capable of receiving waves at least from a space above the seat, each of said ultrasonic sensors being arranged at a different location.

12. The vehicle of claim 11, wherein a first one of said two ultrasonic sensors is arranged on or adjacent to a ceiling of the vehicle and a second one of said two ultrasonic sensors is arranged at a different location in the vehicle such that an axis connecting said first and second ultrasonic sensors is substantially parallel to a second axis traversing a volume in the vehicle above the seat.

13. The vehicle of claim 12, wherein said second ultrasonic sensor is arranged on an instrument panel of the vehicle.

14. The vehicle of claim 13, wherein said transducers further include a third ultrasonic sensor arranged on an interior side surface of the passenger compartment.

15. The vehicle of claim 14, wherein said transducers further include a fourth ultrasonic sensor arranged on or adjacent an interior side surface of the passenger compartment.

16. The vehicle of claim 11, wherein said ultrasonic sensors are capable of transmitting waves at least into the space above the seat.

17. The vehicle of claim 11, wherein said ultrasonic sensors are aimed such that the ultrasonic fields generated thereby cover a substantial portion of the volume surrounding the seat.

18. The vehicle of claim 11, wherein the system further comprises horns for adjusting the transducer field angles of said ultrasonic sensors to reduce reflections off of fixed surfaces within the vehicle.

19. The vehicle of claim 11, wherein the system further comprises grills for adjusting the transducer field angles of said ultrasonic sensors.

20. The vehicle of claim 1, wherein said transducers include four ultrasonic sensors capable of receiving waves at least from a space above the seat, said ultrasonic sensors being arranged at corners of an approximate rhombus which surrounds the seat.

21. The vehicle of claim 1, wherein said transducers include a plurality of ultrasonic sensors capable of transmitting waves at least into a space above the seat and receiving waves at least from the space above the seat, each of said ultrasonic sensors being arranged at a different location, said ultrasonic sensors having different transmitting and receiving frequencies and being arranged in the vehicle such that sensors having adjacent transmitting and receiving frequencies are not within a direct ultrasonic field of each other.

22. The vehicle of claim 1, wherein the trained pattern recognition algorithm is a neural network or neural fuzzy algorithm.

23. The vehicle of claim 1, wherein at least one of said transducers is a capacitive sensor.

24. The vehicle of claim 1, wherein said transducers are selected from a group consisting of seat belt buckle sensors, seatbelt payout sensors, infrared sensors, inductive sensors and radar sensors.

25. The vehicle of claim 1, further comprising control means coupled to said processor means for controlling a component or device in the vehicle in consideration of the output indicative of the current occupancy state of the seat obtained from said processor means.

26. The vehicle of claim 25, wherein the component or device is an airbag system including at least one deployable airbag and said control means control at least one parameter of the deployment of said at least one airbag including the inflation rate, the deflation rate, the incoming gas flow rate and the exiting gas flow rate.

27. The vehicle of claim 1, wherein said transducers include sensors capable of receiving waves modified by passing through a space above the seat.

28. The vehicle of claim 1, wherein said plurality of transducers includes a wave-receiving transducer and a non-wave-receiving transducer.

29. A system for determining the occupancy state of a seat in a vehicle in combination with the vehicle, the system comprising:

a plurality of transducers arranged in the vehicle, each of said transducers generating only a single stream of data relating to the occupancy state of the seat, and

processor means coupled to said transducers for receiving only the single stream of data from each of said transducers such that the stream of data from each of said transducers is passed to said processor means from said transducer without combining with another stream of data and processing the streams of data to obtain an output indicative of the current occupancy state of the seat, said processor means comprising an algorithm created from a plurality of data sets, each of said data sets representing a different occupancy state of the seat and being formed from separate streams of data, each only from one of said transducers, while the seat is in that occupancy state,

said algorithm producing the output indicative of the current occupancy state of the seat upon inputting a data set representing the current occupancy state of the seat and being formed from separate streams of data, each only from one of said transducers.

30. The vehicle of claim **29**, wherein said algorithm is a neural network or neural fuzzy algorithm.

31. The vehicle of claim **29**, wherein one of said transducers is a weight sensor arranged in the seat.

32. The vehicle of claim **29**, wherein one of said transducers is a reclining angle detecting sensor for detecting a tilt angle of a back portion of the seat.

33. The vehicle of claim **29**, wherein one of said transducers is a seat position sensor for detecting the position of the seat relative to a fixed reference point in the vehicle.

34. The vehicle of claim **29**, wherein said transducers include a plurality of weight sensors, each of said weight sensors measuring the weight applied onto the seat at a different location.

35. The vehicle of claim **29**, wherein said transducers include a weight sensor arranged to measure the weight applied to a surface of a seat portion of the seat.

36. The vehicle of claim **29**, wherein said transducers include a force, pressure or strain gage arranged to measure the weight applied to the entire seat.

37. The vehicle of claim **29**, wherein said transducers include a plurality of electromagnetic wave sensors capable of receiving waves at least from a space above the seat, each of said electromagnetic wave sensors being arranged at a different location.

38. The vehicle of claim **29**, wherein said transducers include at least two ultrasonic sensors capable of receiving waves at least from a space above the seat, each of said ultrasonic sensors being arranged at a different location.

39. The vehicle of claim **38**, wherein a first one of said two ultrasonic sensors is arranged on or adjacent to a ceiling of the vehicle and a second one of said two ultrasonic sensors is arranged at a different location in the vehicle such that an axis connecting said first and second ultrasonic sensors is substantially parallel to a second axis traversing a volume in the vehicle above the seat.

40. The vehicle of claim **38**, wherein the system further comprises horns for adjusting the transducer field angles of said ultrasonic sensors to reduce reflections off of fixed surfaces within the vehicle.

41. The vehicle of claim **29**, wherein said transducers include a plurality of ultrasonic sensors capable of transmitting waves at least into a space above the seat and receiving waves at least from the space above the seat, each of said ultrasonic sensors being arranged at a different location, said ultrasonic sensors having different transmitting and receiving frequencies and being arranged in the vehicle such that sensors having adjacent transmitting and receiving frequencies are not within a direct ultrasonic field of each other.

42. The vehicle of claim **29**, wherein at least one of said transducers is a capacitive sensor.

43. The vehicle of claim **29**, wherein said transducers are selected from a group consisting of seat belt buckle sensors, seatbelt payout sensors, infrared sensors, inductive sensors and radar sensors.

44. The vehicle of claim **29**, further comprising control means coupled to said processor means for controlling a component or device in the vehicle in consideration of the output indicative of the current occupancy state of the seat obtained from said processor means.

45. The vehicle of claim **44**, wherein the component or device is an airbag system including at least one deployable airbag, said control means controlling at least one parameter of the deployment of said at least one airbag including the inflation rate, the deflation rate, the incoming gas flow rate and the exiting gas flow rate.

46. The vehicle of claim **29**, wherein said transducers include sensors capable of receiving waves modified by passing through a space above the seat.

47. The vehicle of claim **29**, wherein said plurality of transducers includes a wave-receiving transducer and a non-wave-receiving transducer.

48. The vehicle of claim **29**, wherein said algorithm is a trained pattern recognition algorithm.

49. A system for determining the occupancy state of a seat in a vehicle in combination with the vehicle, the system comprising:

a plurality of transducers including at least two wave-receiving transducers arranged in the vehicle, each of said transducers providing data relating to the occupancy state of the seat, a first one of said wave-receiving transducers being arranged over a front portion of the seat or in front of the seat and a second one of said wave-receiving transducers being arranged over a rear portion of the seat or behind the seat, and

a processor coupled to said transducers for receiving data from said transducers and processing the data to obtain an output indicative of the current occupancy state of the seat, said processor comprising an algorithm which produces the output indicative of the current occupancy state of the seat upon inputting a data set representing the current occupancy state of the seat and being formed from data from said transducers.

50. The vehicle of claim **49**, wherein said algorithm is created from a plurality of data sets, each of said data sets representing a different occupancy state of the seat and being formed from data from said transducers while the seat is in that occupancy state.

51. The vehicle of claim **49**, wherein said first and second wave-receiving transducers are arranged to receive ultrasonic waves.

52. The vehicle of claim **49**, wherein each of said transducers generates only a single stream of data relating to the occupancy state of the seat and said processor means are arranged to accept only the single stream of data from each of said transducers such that the stream of data from each of said transducers is passed to said processor means without combining with another stream of data.

53. The vehicle of claim **49**, wherein said first wave-receiving transducer is arranged on an instrument panel of the vehicle.

54. The vehicle of claim **49**, wherein said plurality of transducers further includes a third wave-receiving transducer arranged on an interior side surface of the passenger compartment.

55. The vehicle of claim 54, wherein said plurality of transducers further includes a fourth wave-receiving transducer arranged on or adjacent an interior side surface of the passenger compartment.

56. The vehicle of claim 49, wherein said wave-receiving transducers are capable of transmitting waves at least into the space above the seat.

57. The vehicle of claim 56, wherein said wave-receiving transducers are aimed such that the wave fields generated thereby cover a substantial portion of the volume surrounding the seat.

58. The vehicle of claim 49, wherein the system further comprises horns for adjusting the transducer field angles of said wave-receiving transducers to reduce reflections off of fixed surfaces within the vehicle.

59. The vehicle of claim 49, wherein the system further comprises grills for adjusting the transducer field angles of said wave-receiving transducers to reduce reflections off of fixed surfaces within the vehicle.

60. The vehicle of claim 49, wherein said plurality of transducers includes a weight sensor arranged in the seat.

61. The vehicle of claim 49, wherein said plurality of transducers includes a reclining angle detecting sensor for detecting a tilt angle of a back portion of the seat.

62. The vehicle of claim 49, wherein said plurality of transducers includes a seat position sensor for detecting the position of the seat relative to a fixed reference point in the vehicle.

63. The vehicle of claim 49, wherein said plurality of transducers includes a plurality of weight sensors, each of said weight sensors measuring the weight applied onto the seat at a different location.

64. The vehicle of claim 49, wherein said plurality of transducers includes a weight sensor arranged to measure the weight applied to a surface of a seat portion of the seat.

65. The vehicle of claim 49, wherein said plurality of transducers includes a force, pressure or strain gage arranged to measure the weight of the entire seat.

66. A system for determining the occupancy state of a seat in a vehicle in combination with the vehicle, the system comprising:

a plurality of transducers including at least two wave-receiving transducers, each of said transducers providing data relating to the occupancy state of the seat, a first one of said wave-receiving transducers being arranged on a top of a dashboard or instrument panel of the vehicle and a second one of said wave-receiving transducers being arranged at a different location in the vehicle such that an axis connecting said first and second wave-receiving transducers passes through a volume above the seat; and

a processor coupled to said transducers for receiving data from said transducers and processing the data to obtain an output indicative of the current occupancy state of the seat, said processor comprising an algorithm which produces the output indicative of the current occupancy state of the seat upon inputting a data set representing the current occupancy state of the seat and being formed from data from said transducers.

67. The vehicle of claim 66, wherein each of said transducers generates only a single stream of data relating to the occupancy state of the seat and said processor means are arranged to accept only the single stream of data from each of said transducers such that the stream of data from each of said transducers is passed to said processor means without combining with another stream of data.

68. The vehicle of claim 66, wherein said second wave-receiving transducer is arranged on a ceiling of the vehicle.

69. A system for determining the occupancy state of a seat in a vehicle in combination with the vehicle, the system comprising:

a plurality of transducers arranged in the vehicle, each of said transducers providing data relating to the occupancy state of the seat, at least one of said transducers being a capacitive or electric field sensor; and

processor means coupled to said transducers for receiving the data from said transducers and processing the data to obtain an output indicative of the current occupancy state of the seat, said processor means comprising an algorithm created from a plurality of data sets, each of said data sets representing a different occupancy state of the seat and being formed from data from said transducers while the seat is in that occupancy state,

said algorithm producing the output indicative of the current occupancy state of the seat upon inputting a data set representing the current occupancy state of the seat and being formed from data from said transducers.

70. A system for determining the occupancy state of a seat in a vehicle in combination with the vehicle, the system comprising:

a plurality of transducers arranged in the vehicle, each of said transducers providing data relating to the occupancy state of the seat, at least one of said transducers being selected from a group consisting of seat belt buckle sensors, seatbelt payout sensors and inductive sensors; and

processor means coupled to said transducers for receiving the data from said transducers and processing the data to obtain an output indicative of the current occupancy state of the seat, said processor means comprising an algorithm created from a plurality of data sets, each of said data sets representing a different occupancy state of the seat and being formed from data from said transducers while the seat is in that occupancy state,

said algorithm producing the output indicative of the current occupancy state of the seat upon inputting a data set representing the current occupancy state of the seat and being formed from data from said transducers.

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